OBSTRUCTIVE SLEEP APNEA DETECTION APPARATUS AND METHOD USING PATTERN RECOGNITION

Inventors: Ahmet Karakasoglu

This invention relates to an obstructive sleep apnea detection apparatus method utilizing pattern recognition.

In application Serial No. 08/472,441 filed on
5   June 7, 1995 there is disclosed a sleep apnea screening and/or detecting apparatus and method, which has been found to have many desirable features. However, there are limitations in the apparatus and method, particularly where shallow breathing sounds are being
10   monitored. Also, in certain situations there has been difficulty in eliminating background noise or reducing it to a sufficiently low level. There is therefore a need for a new apparatus and method which overcomes these difficulties.

15   In general, it is an object of the present invention to provide an obstructive sleep apnea detection apparatus and method which utilizes pattern recognition to make it possible to monitor shallow and wide ranges of airflows of the patient producing various
20   sound levels and/or vibration caused by turbulence in the airflow.

A-64721/HCH

Another object of the invention is to provide an apparatus and method of the above character which makes possible unattended home studies of obstructive sleep apnea and hypopnea.

5   Another object of the invention is to provide an apparatus and method of the above character which only utilizes airflow and/or oxygen saturation sound information for detecting disordered breathing events.

Another object of the invention is to provide an
10   apparatus and method of the above character in which a single vibration sensor can be utilized for measuring turbulence in airflow.

Another object of the invention is to provide an apparatus and method of the above character which may
15   only require the use of a single microphone for picking up the desired signal and ambient noise.

Another object of the invention is to provide an apparatus and method of the above character in which the noise component is eliminated internally in software to
20   provide improved noise cancellation, especially for periodic noises.

Additional objects and features of the invention will appear from the following description in which the preferred embodiments are set forth in detail in
25   conjunction with the accompanying drawings.

Figure 1 is a block diagram of an obstructive sleep apnea detection apparatus incorporating the present invention and showing overall system architecture.

A-64721/HCH

4

Figure 2A is a block diagram of an active noise cancellation unit utilized in the obstructive sleep apnea detection apparatus of Figure 1.

Figure 2B is an alternative embodiment of an active noise cancellation unit for use in the obstructive sleep apnea detector of Figure 1.

Figure 3 is a block diagram of a wavelet transform-based feature extractor utilized in the apparatus shown in Figure 1.

Figure 4 is a schematic diagram of a neural network-based pattern recognizer utilized in the apparatus shown in Figure 1.

In general the apparatus for detecting a breath pattern of a breathing patient having lungs and a nose and mouth in communication with the lungs and breathing through the nose and/or mouth and creating an airflow into and out of the lungs is comprised of a first sensor in close proximity to the face of the patient for monitoring the airflow to provide a first channel of airflow information in an analog format. Analog-to-digital conversion means is provided for converting the first channel of airflow information in an analog format into a first channel of airflow information in a digital format. Means is provided for filtering the airflow in the digital format in the first channel of information to improve the signal-to-noise ratio of the signal to provide filtered airflow information. Means operates on the filtered airflow information for estimating the

A-64721/HCH

5

amount of airflow volume inhaled and exhaled by the patient to provide a signal representing the estimated volume of air. A wavelet transform feature extractor is provided to obtain a continuous time wavelet transform

5 of the estimated volume of air for ascertaining whether a breathing pattern has been recognized and providing a breathing pattern signal. A neural network pattern recognizer operates on the breathing pattern signal to ascertain when disordered breathing is occurring and

10 providing a disordered breathing signal. Means operates on the disordered breathing signal to separate the disordered breathing into apnea and hypopnea categories.

More specifically, the obstructive sleep apnea detection apparatus 16 incorporating the present

15 invention is shown in block diagram form in Figure 1 and as shown consists of an aerial microphone 17 which is utilized to sense breathing or snoring sounds of the patient to provide a first channel of input information. The microphone 17 is located anywhere between 0-2 feet

20 from the patient's head. Additional sound information for a second channel of input information is obtained from a suitable source such as a tracheal microphone 18 located on the patient's neck externally of the patient's trachea. Alternatively, the microphone 18 can

25 be used for picking up ambient sound.

The microphone 17 in the alternative can be a piezoelectric vibration sensor which is immune to sound and thus eliminates the need for the ambient sound

A-64721/HCH

6

sensor 18. The sensor 18 thus senses turbulence in the airflow of the breathing person. A third channel of input information can be received from an oxygen saturation sensor 19 which is positioned on an

5 appropriate location on the body of the patient, such as an earlobe or a finger.

Audible sound signals from the body of the patient are converted by the microphones 17 and 18 to electrical signals which are supplied to two parallel circuits 21

10 and 22 as shown in Figure 1 with each parallel circuit consisting of an analog-to-digital (A/D) converter 26. The output from the A/D converter 26 is supplied to an active noise cancellation unit 27 in which background noise is suppressed and the useful information, i.e.,

15 the breathing or snoring sound signals are extracted and supplied to a filter bank 28 in which the signals are band pass filtered to adjust the filter band to a desired signal characteristic to further improve the signal-to-noise ratio. The output from the filter bank

20 28 is supplied to an estimated volume of airflow (EVA) waveform generation unit 29 which provides an estimate of acoustical energy representing the amount of air volume inhaled and exhaled by the patient to ascertain whether or not the patient's breathing is apneic.

25 The output from the oxygen saturation sensor 19 is supplied to an A/D converter 31 which supplies its output to a pre-processing filtering unit 32. The outputs from the EVA waveform generation units 29 and

A-64721/HCH

7

the pre-processing filtering unit 32 are supplied in parallel to a wavelet feature extractor 36 and a logarithmic converter 37. The outputs of the extractor 36 and the converter 37 are supplied to a neural network

5 pattern recognizer 38 that has its output supplied to a k-means pattern classifier 39 which also receives the outputs from the EVA waveform generation units 29 and the pre-processing and filtering unit 32, as shown. The output of the k-means pattern classifier is supplied to

10 an events counting and storage unit 41 which records abnormal (apnea) breathing/snoring patterns.

The active noise cancellation unit 27 of Figure 1 is shown in more detail in Figure 2A and consists of a single input from the output of the A/D converter 26

15 identified as a "signal source" which as shown is the microphone 17 that picks up the respiration signal as well as ambient noise. The input to the noise cancellation unit 27 is supplied to a summer or adder 51 and is also supplied to a delay unit 52 which is used to

20 ensure that the active noise cancellation unit 27 will predict future values for the output of the noise cancellation unit 27. The output of the delay unit 52 is supplied to an adaptive linear filter 53 which has its output on line 54 connected to the adder 51. The

25 output from the adder 51 is supplied to an output signal line 56 to the filter bank 26. The output on the output signal line 56 is also supplied by a line 57 connected

A-64721/HCH

to the adaptive linear filter 53 to provide an
adaptation signal.

The active noise cancellation unit 27 is utilized
to remove background noise and operates on the signal
5 supplied by the sensing microphone 17. The adaptive
linear filter 28 uses the output signal on the line 56
to produce an estimate of the periodic ambient noise
which is in turn subtracted from the sensor output from
the sensing microphone 17 in the adder 51. The output
10 on the line 57 is used to adjust the tap weights in the
adaptive linear filter 38 to minimize the mean-square
value of the overall output on the signal line 56 to
cause the overall output to be the best estimate of the
desired signal in the minimum mean-square sense.

15 The adaptive linear filter 28 is in the form of a
transversal filter consisting of a set of delay line
elements each of which is represented by one sampling
period of delay and a corresponding set of adjustable
coefficients. At the sampling time instant k, the
20 available signal consists of a set of samples:

$u(k), u(k-1), u(k-2) \ldots u(k-n)$

These samples are convolved with a corresponding set of
adjustable tap weights:

$w_1, w_1, w_2 \ldots w_n$

25 to produce an output signal sequence, $y(n)$. The signal
collected by the breathing/snoring microphone 17 can be
designated as $d(n)$. The filter output $y(n)$ is compared
with the $d(n)$ to produce an estimation error $e(n)$ which

A-64721/HCH

is used by the adaptive algorithm to thereby control the corrections applied to the individual tap weights. This process is continued until the noise estimation error e(n) becomes sufficiently small, as for example

5   $1/2^{16}$ = 1.5×10^{-5}. In order to keep the estimation algorithm causal during its operation, an internal time delay, d, supplied by the delay unit 52 is added to the reference input signal supplied by the A/D converter 23. The time duration of d is selected according to the

10 desired sampling rate. When the acoustical properties of the environment in which the microphone 17 is positioned changes, the adaptive algorithm which is used to adjust the coefficients has the added task of continually tracking the variations occurring in the

15 environment being sensed by the microphone 17. For this reason, a normalized adaptation step size, as for example as defined in "Adaptive Signals & Systems" (Widrow & Stearns, Prentice Hall, 1978), has been used to improve the convergence rate for the active noise

20 cancellation unit 27.

An alternative active noise cancellation unit 27a is shown in Figure 2B which is supplied signal and noise information from the first and second input channels provided by the respiration sensor 17 and the ambient

25 sound sensor 18 respectively identified as primary source and secondary source. The signal from the primary source is delivered to the delay unit 52a and thence to the summer or adder 51a. The signal from the

A-64721/HCH

10

secondary source is delivered to the adaptive filter 53a which delivers its output to the summer 51a. The line 57a supplies an adaptation signal to the adaptive filter 53a.

5   It has been found that the useful portion of the breathing/snoring sound spectrum from human beings is within the frequency band of 200 Hz to 1500 Hz. The filter bank 28 which receives the signal from the active noise cancellation unit 27 consists of a plurality of

10   band pass filters, as for example 13 filters each having a bandwidth of 100 Hz and having cutoff frequencies from 300 Hz to 1500 Hz. When the signal from the active noise cancellation unit 27 arrives at the filter bank 28, a signal is supplied to each of the 13 filters and

15   corresponding outputs are computed. Since the input signals are known, the filter that yields the best signal-to-noise ratio is selected and is used for a predetermined period, as for example, the next three minutes. At the end of this predetermined period, the

20   selection process is repeated in order to accommodate any possible variations in sound characteristics which have occurred.

The filters are realized by using Butterworth's technique.

25

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + \ldots + a_6 y(k-6) + b_0 u(k) + b_1 u(k-1) + \ldots + b_6 u(k-6)$$

<div align="right">Equation 1</div>

A-64721/HCH

11

For the present application, the a_i and b_i coefficients are calculated using conventional Matlab routines to realize the above-mentioned characteristics for a third order filter.

5   In order to determine if the patient's breathing is disordered, the amount of air volume inhaled and exhaled by the patient needs to be known. The output from the filter bank 28 supplies a microphone signal which has been processed to remove the artifacts. The EVA

10   waveform generation unit 29 generates a waveform from the air volume inhaled and exhaled by the patient. A scoring methodology is used which closely mimics the results of the methodology of a conventional sleep study involving a standard polysomnograph (PSG). In

15   accordance with the present invention, a prediction sequence has been utilized which generates the estimated volume of airflow (EVA) waveforms which closely follow the actual air volume that is inhaled or exhaled by the patient.

20   The software code utilized in the present invention implements the following equation to obtain the EVA waveform:

$$\sigma(k) = \alpha_1\, \sigma(k-1) + \alpha_2\, \sigma(k-2) + \alpha_3\sigma(k-3) + \beta\,|x(k)|$$

25   <u>Equation 2</u>

where k is current sampling instant, k-1 is the previous sampling instant, etc., $\alpha(k)$ is the current estimate of airflow, $x(k)$ is the current microphone sample, α and β

A-64721/HCH

12

are user defined parameters that change the shape of the
waveforms. Having

$\alpha_1=0.9$, $\alpha_2=0.05$, $\alpha_3=0.03$, $\alpha_4=0.01$ and $\beta=0.01$

were suitable choices for obtaining a waveform that
5   closely resembles the airflow waveforms that are
obtained by using an airflow meter.

The signal noise from the trachea microphone 18 is
treated in a similar manner as the signal and noise from
the aerial microphone 17. The information from the
10 oxygen saturation sensor 19 is supplied to the wavelet
feature extractor 36 thence to the neural network
pattern recognizer 38 and the k-means pattern classifier
39 and the event counting and storage 41 all serve as
pattern classification means. The logarithmic pattern
15 converter 37 creates a logarithmic scaling of sound
levels. The dynamic range of the signals received from
the sensors 17, 18 and 14 is greatly improved by
converting the signals received from the sensors 17, 18
and 19 to a logarithmic scale which greatly increases
20 the accuracy of the pattern classification. To obtain a
logarithmic scale signal, the EVA signal, f(t) is
subjected to the following conversion:

$$d(t) = (1/\log 2)\log[f(t)] = 3.2193 \log [f(t)]$$

25   Equation 3

Thus, the outputs from the EVA waveform generation
units 29 can be identified as f(t) and the output from

A-64721/HCH

13

the logarithmic converter 37 can be characterized as a
logarithmic curve, d(t).

The wavelet feature extractor 36 is particularly

helpful in analyzing transient signals with short time

5   behavior. The wavelet feature extractor 36 forms a

continuous-time wavelet transform of the EVA signal f(t)

with respect to the wavelet g(t) which is defined as:

$$Wg\ f(a,b) = \frac{1}{\sqrt{(e)}} \int_{-\infty}^{\infty} f(t)\ g\left(\frac{t-b}{a}\right) dt$$

Equation 4

where $g\left(\frac{t-b}{a}\right)$ is obtained from the mother wavelet g(t)

satisfying

$$F[g(t)] = G(w)\ ;\ \int_{-\infty}^{\infty} \frac{|G(w)|^2}{|w|} < \infty$$

Equation 5

The wavelet transform (WT) is used as a pre-
processor for the neural network pattern classifier 38.
The wavelet decomposition of an EVA cycle is used as an
30   input in order to obtain apnea/hypopnea events with
respect to time.

A representation of the wavelet transform-based
feature extractor 36 is shown in Figure 3 and as shown
consists of upsampling, downsampling and filtering
35   units. It is adaptive and can be trained to extract
breathing events from a breath pattern. As shown, the
three inputs to the wavelet transform-based feature
extractor as shown in Figure 3 showing the architecture

A-64721/HCH

by which the equations hereinbefore set forth are
implemented. As shown, the architecture of the
extractor 36 separates the inputs into two frequency
bands represented by the upper branch or path 71 and the
5   lower branch or path 72. The upper branch or path is
separated into two additional frequency bands
represented by branches or paths 73 and 74 which are
combined in a summer 76 into a single branch 77 which is
combined with the branch 72 and a summer 78 to provide a
10 single output on a line 79. The branch 71 includes an
estimated value filter 81 having a symbol therein as
indicated and a downsampling estimator 82 having a
symbol therein as shown. Similarly the branch 72 has an
estimated value filter 83 which feeds into a
15 downsampling estimator 84, both having symbols therein
which represent the functions performed thereby.

As pointed out previously the branch 72 divides
into two different frequency branches 73 and 74 with the
branch 73 having an estimated value filter 86 followed
20 by an upsampling estimator 87 which feeds its output
into an actual value filter 88. Similarly the branch 74
is provided with an estimated value filter 91 followed
by an upsampling estimator 92 followed by an actual
value filter 93. The various components of the branches
25 73 and 74 are labeled with appropriate indicia to
indicate these functions. A branch 77 following the
summer 76 is provided with an upsampling estimator 96
followed by an estimated filter value filter 97 which

A-64721/HCH

feeds its output into the summer 78. The estimator 84
in the branch 72 supplies its output to an upsampling
estimator 101 which feeds its output into an actual
value filter 102 which supplies its output to the summer
5   78.

From the foregoing it can be seen that the input
signals are split into two frequency subbands and that
the subband signals are processed in the manner shown in
Figure 3 by incrementing or increasing or decrementing
10 or decreasing and processing the frequency bands to
obtain the desired information and thereafter combining
or reconstructing the signal from the subbands by the
use of the summers or adders 76 and 78 respectively.

Thus on the output line 79, there is a full
15 reconstructed signal which has been reconstructed from
the subbands as shown in Figure 3. By providing
subbands in multiples of two, it is possible to process
information in each frequency subband to obtain the
desired hidden information and thereafter to recombine
20 the subbands to provide the signal in its original form.
Thus the wavelet transform-based feature extractor
rather than operating on the original signal as a whole
or total, splits that signal into frequency subbands as
hereinbefore described and extracts therefrom disordered
25 breathing events from a given breath pattern or breath
signal. Using this extracted information, the neural
network-based pattern recognizer analyzes the extracted
disordered breathing events to ascertain whether or not

A-64721/HCH

16

apnea or hypopnea have occurred. Thus it can be seen that the combination of the feature extractor 36 and the pattern recognizer 38 ascertain first whether or not there is a breath pattern and secondly if it is a normal

5 breath pattern or apnea or hypopnea. Thus the feature extractor 36 provides the information set and the pattern recognizer ascertains whether or not the information set is a normal breath and if not, whether or not it is apnea or hypopnea.

10 The pattern recognizer 38 includes an input 79 from the feature extractor 36 and an input 106 from the logarithmic converter 37 which is combined as shown in Figure 4 into a single input into a delay network 107 consisting of a plurality of individual delays 108

15 designated d^0 standing for zero delay, d^1 for a one-step delay, d^2 for a two-step delay, up through an infinite number of delays to delay d^k. The signals after being delayed in this manner are supplied to a first layer 111 neurons 112 which are weighted from n_1 to n_k and are then

20 distributed to a second layer 116 of neurons 117 identified as N_1 through N_m through weighted synapsis connectors 121 which are weighted from W_{11} to W_{km}. As shown in Figure 4, the two layers 111 and 116 of neurons are provided to give nonlinearity. The signals after

25 being processed by the second layer 116 are reconstructed with h's, namely h_1 through h_m signals to a summer 126 to provide an output on line 127.

A-64721/HCH

17

The wavelet feature extractor 36 in combination
with the neural network pattern recognizer 38 makes
possible pattern recognition without the use of preset
thresholds. Rather it is an adaptive system which

5   provides a trained or teached network. Thus with the
feature extractor 36 and the pattern recognizer 38, the
apparatus can be supplied with a few samples of
disordered breathing events and from that it learns how
to differentiate a healthy breath from a disordered

10 breathing event. As the system or apparatus is trained,
the synapses between the layers of neurons are adjusted
by adjusting the weights of the synapses. Thus the
neural network can readily differentiate between a
normal breath signal, an abnormal breath signal, a

15 breath signal with apnea and a breath signal with
hypopnea. The system or apparatus of the present
invention is capable of adjusting between these
patterns. It can readily do this by itself by
adaptively adjusting its own synapses.

20   The neural network can be readily taught by having
a technician classify certain breathing events by
examining the breathing pattern of one or more patients
and classifying the breathing with normal breathing,
abnormal breathing and breathing with apnea or breathing

25 with hypopnea. Using this information and supplying the
same to the apparatus as shown in Figure 1, the neural
network can be readily trained and thereafter, the

A-64721/HCH

neural network need only adapt to each individual's breathing habits which are being monitored.

In the system architecture shown in Figure 1, the neural network pattern recognizer generally separates

5   the signals into two categories, normal breath versus disordered breath, and the k-means pattern classifier 39 separates the disordered breath into apnea and hypopnea categories. Each event so classified by the pattern classifier 39 is counted in the event counting and

10   storage unit 41.

The logarithmic converter 37 converts the same breathing signal which is received by the wavelet feature extractor 36 and converts the signal to a logarithmic signal. The logarithmic signal is nonlinear

15   and thus can reach saturation and thus in effect acts like a compressor to compress the signal into a smaller variation or narrower range which is not be obtainable from the wavelet feature extractor 36 or the neural network pattern recognizer 38 to thereby provide a more

20   reliable output from the neural network pattern recognizer 38. Thus the neural network pattern recognizer 38 which receives the output from the wavelet feature extractor 36 and the logarithmic converter 37 as shown in Figure 4. The neural network pattern

25   recognizer 38 consists of nonlinear nodes and convolution units.

The neural network pattern recognizer 38 receives the EVA waveform and information regarding its frequency

A-64721/HCH

19

characteristics and determines if a given sound pattern represents a respiration sound. The neural network pattern recognizer 38 is trained by utilizing known respiration patterns to provide appropriate weights in

5 order to decide if a given sound signal is any kind of breath signal. Directly measured airflow curves and published breathing statistics are utilized in training the neural network pattern recognizer 38.

The k-means pattern classifier 39 is used in

10 conjunction with the neural network pattern recognizer 38. In the k-means pattern classifier 39, the distance of the center of gravity point of each given event with reference events are measured and a decision is made whether the event is

15   (a) a healthy breathing event

    (b) a hypopnea event or

    (c) an apnea event.

In connection with the classifier 39, the standard polysomniograph decisions were used as reference events

20 when measuring the Euclidian distances which are defined as

$$L(t) = [(d_1)^2 = (d_2)^2 + \ldots + (d_m)^2]^{1/2}$$

Equation 6

25   From the foregoing, it can be seen that there has been provided an obstructive sleep apnea detection apparatus and method using pattern recognition. This pattern recognition makes it possible to monitor shallow

A-64721/HCH

20

and wide ranges of airflow of the patient. The

apparatus and method is relatively simple so that it can

be utilized in conjunction with unattended home studies.

When microphones are used, the noise component is

5   eliminated internally in software to provide improved

.noise cancellation, particularly for periodic noises.

A-64721/HCH